A Hybrid Method integrating Industry 4.0's Energy Digitization

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Abstract: - Industrial firms must face important environmental challenges (greenhouse gas emissions, energy efficiency) and business imperatives. For this sector to accomplish a lower-cost energy transition, digitalization is a key lever.

Today, the fourth industrial revolution is constructing a forward-thinking first industry known as industry 4.0, which combines many developing technologies to produce digital and efficient solutions.

In this paper, we examine the impact of Industry 4.0 on the evolution of a new simulation modeling paradigm embodied by the concept of Digital Twin.

To begin, we will discuss the industry 4.0 paradigm, its history, current state of development, and its impact on the development of the simulation modeling paradigm.

A needs-based approach can result in the faster, deeper, and more extensive implementation of efficient systems.

Furthermore, we present the methodology's multiple case studies and discuss several research and development projects involving the modeling of automated industrial processes that have been presented in recent scientific publications.

The lack of tools, however, is not a problem because the current generation of general-purpose simulation modeling tools provides adequate integration options. However, to build on several physical levels of the integrated model system, close collaboration between academia and industrial partners is required to demonstrate industry and scientific community acceptance of the new analog modeling paradigm.

Adoption and development of relevant morality in a needs-based process can lead to more efficient industrial automation implementation that is faster, deeper, and more extensive.

Keywords: - Industry 4.0, Digital Twin, SME (Small and Medium-sized Enterprises), energy digitalized, simulation and modeling; automated modeling

ICT: Information and communication technologies, OEMs: original equipment manufacturers, CPS: cyber-physical system, CPPS: physical production systems, DES: discrete event simulation, SQL: Structured Query Language, XML: Extensible Markup Language, ABM: Agent-Based Modeling, CMSD: Core Manufacturing Simulation Data, UML: Unified Modeling Language, MES: Manufacturing Execution System, ERP: Enterprise Resource Planning

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1 Introduction

Digital transformation is the primary lever for optimizing a sustainable economy in an industrial context. Most industries currently only use 10% of their data, preventing them from taking meaningful action [8].

As a result, the first and most important step in the industry's digital transformation is to collect and manage all data, and it is necessary to be able to retrieve and store all of this information in a single, highly secure location.

The use of models of real or fictional systems, or processes to better understand, or predict the behaviors of a modeled system or process is known as simulation modeling in engineering can reduce costs, and consumption, shorten development cycles, improve product quality, and greatly simplify knowledge management.

This article will describe the developments of Industry 4.0 and the Fourth Industrial Revolution that have led to new simulation modeling paradigms, embodied by the concept of digital twins, and will validate the adoption of new simulation modeling paradigms in the industrial and scientific communities through multiple case study by presenting real cases of Industry 4.0 method and technology application [15].

2 The position of SMEs (Small and Medium-sized Enterprises) in Industry 4.0

Today, the position of SMEs (small and medium-sized enterprises) in Industry 4.0 is of particular concern, because the level of automation of SMEs is generally low and their funds are limited, but SMEs represent an important part of the creation of jobs and value [8].

Information and communication technologies (ICT) and automation technologies are completely integrated into the factory of the future. All systems, including R&D, as well as business partners, suppliers, original equipment manufacturers (OEMs), and customers, are networked and consolidated [8].

According to KPMG, manufacturing networking and transparency enable a paradigm shift from "centralized" to "local" production.

Manufacturing now employs "embedded systems," which collect and transmit specific data. A central computer in the future factory coordinates the intelligent networking of all subsystems into a cyber-physical system (CPS) capable of increasing independence [15].

CPS refers to the networking of various integrated software systems that collect and transmit data. A paradigm shift from "centralized" to "local" production is thus taking place, and a central information system manages an intelligent network while taking physical factors into account, such as the capture of needs via man-machine interfaces that allow independent process management [8].

The close interaction of the physical and virtual worlds represents a fundamentally new aspect of the manufacturing process known as "CPS" physical production systems. Because many SMEs are still using older proprietary systems, the emergence of Industry 4.0 networking and integration standards, as well as open standards architectures, has the potential to benefit them.

SMEs can become temporary production networks with precisely calculated value-added contributions, allowing them to significantly reduce their production management efforts while meeting much higher market demands [8].

Furthermore, additive manufacturing and flexible machines enable the production of very small series and personalized products at unit costs previously only possible in large series.

3 Green technology trends in Industry 4.0

Large battery-powered sensor networks can now be built using new energy-efficient green computing technologies. A major shortcoming is the general lack of standards. Many aspects of Industry 4.0 technology are already in place, but some areas still require binding international standards. Industry 4.0 is currently a concept rather than a product or service that can be purchased [10].

This is due in part to the imprecise definition of "Industry 4.0" and customers' exaggerated expectations. What is certain is that Industry 4.0 necessitates the use of products such as industrial and management software (CAD, virtual simulation tools, etc.), processes, and devices (Ethernet, robotics, relays, motors drives, sensors, switches, etc.). These devices necessitate specialized knowledge of information and communication technologies (ICT) and automation technologies, posing both a challenge and an opportunity for future workforce educators and trainers [10].

4 The modern simulation paradigm

Connectivity of a simulation model in the modern simulation paradigm typically involves integration with a static database of business variables, a user-friendly front end, and additional decision support tools such as expert systems or group decision support systems. Simulation has primarily been used to create stand-alone solutions with limited scope and lifespan. However, as computer simulation has permeated various areas of business processes, the need to link simulation models used in different parts of an organization has arisen [5].

Furthermore, the trend in simulation development has shifted from purely analytical and optimization-oriented models to the integration of simulation models into decision support tools that will be used on a regular basis. A common distributed simulation system, for example, can be built by integrating models of various parts of an organization to perform large-scale business system simulations, providing a complete view of the modeled organization.

As a result, design requirements have shifted from stand-alone models accessible only to simulation experts to models that can be connected to, and even modified by, user-friendly interfaces or other applications [7].

Figure 1 depicts a diagram of such a system.

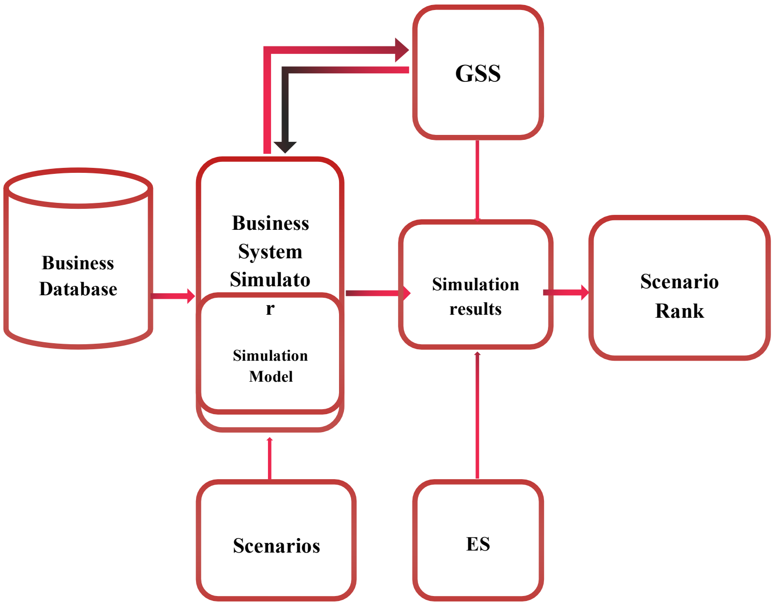

Figure 1: *Schematic of a typical simulation modeling based DSS system*

5 The new "Digital Twin" concept

The best guess is that the new simulation modeling paradigm is the concept of the "Digital Twin," which we will discuss in the following chapters.

The Digital Twin concept extends the use of simulation modeling to all phases of the product life cycle, where products are first developed and tested in detail in a virtual environment, and subsequent phases use the information generated and collected by previous phases [11].

Manufacturers must shift away from traditional design processes and practices that used a "build and modify" approach, and instead adopt a more systemic approach that has been an essential part of the design process in the aerospace and automotive industries. for a long time

To accelerate the development of model and scenario releases, algorithms that create or modify simulation models based on model input data can be developed. This is especially useful for large simulation models and when the variants of the model are prepared by an algorithm, such as an optimization algorithm.

However, automated model creation and modification necessitates that the model structure is modifiable by an algorithm without the need for manual intervention.

These four points summarize the main changes in the simulation and modeling paradigms during the transition from an autonomous simulation-based decision support system to the Digital Twin:

- Integration and connectivity into a larger IS (manufacturing or integrated management software)
- A multi-level/resolution holistic approach, including physical modeling, is used to model the system.
- Several aspects of the simulation model necessitate a high level of detail and a low level of abstraction.
- Model creation and modification are fully automated (data-driven) [11].

6 The Digital Twin simulation

A digital twin is a natural result of using a system design approach to product development, and it can be easily integrated into the final product for training, online diagnostics, performance optimization, and other purposes.

The functional model interface is supported by the majority of industrial automation platforms as a means of integrating Twin so that it can run in parallel with the real machine.

Engineers can use simulation software to create a virtual prototype of the machine design directly from the CAD representation and integrate it as a Digital Twin as a functional mock-up unit on their real-time platform (FMU) [12].

According to Goossens (2017), the cost of developing numerical models of multidisciplinary systems has decreased significantly in recent years due to the introduction of powerful and user-friendly mathematical system modeling tools and general-purpose modeling tools like MATLAB and Analogic.

Identifying and addressing signaling issues early in the Twin's development process is critical. Figure 2 depicts an example of a cyber-physical production system incorporating Digital Twin simulation modeling.

A Digital Twin simulation model of a process or part of a process has several potential uses in an organization:

- Without the expense of a dedicated training simulator, an online digital twin allows an operator to train on a virtual machine until they have the skills and confidence to operate the real machine. Using an in-line Digital Twin speeds up the learning process while reducing the risk of machine damage.
- A digital twin can be used to identify potential problems with its real counterpart by combining optimal control and model predictive control techniques with advanced machine learning capabilities. By detecting a drift between machine performance and model behaviour, a high-fidelity physical model running in parallel with the real machine can immediately indicate a potential malfunction of the real machine. The data can be

used to shut down and repair the faulty machine, or the model can be used to provide a strategy for compensating for a drop in performance without slowing or stopping production.

- An integrated digital twin would serve as the foundation for increasing machine self-awareness, allowing it to optimize its own performance for given duty cycles, diagnose and compensate for non-catastrophic faults, and coordinate operation with other machines while requiring minimal operator intervention.

The business system simulator in such a system employs a Digital Twin model of the business process.

The digital twin is used to provide a detailed, dynamically updated digital representation of the actual business process to the business intelligence toolkit (eg, a manufacturing plant).

Process data is collected in real-time by the array of sensors and intelligent machines in the business process, stored in the enterprise database, and then transmitted to Digital Shadow.

The operation of the Digital Master model is adjusted based on the data contained in the Digital Shadow, enabling online optimization and decision support, as well as process automation control, thereby creating a control feedback loop, which is the foundation of cybernetics.

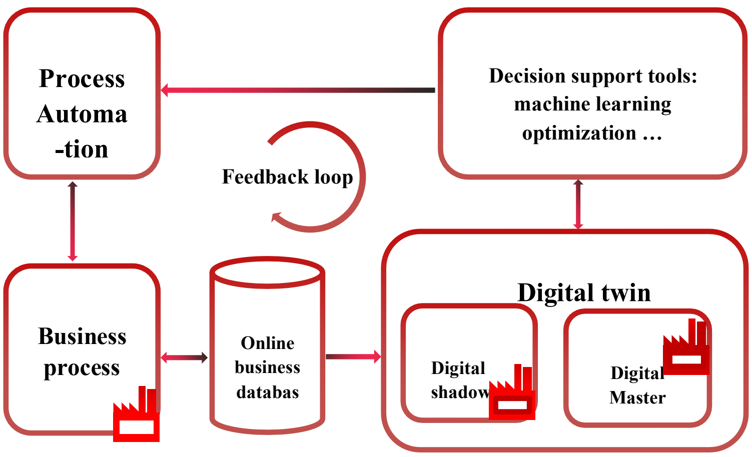

Figure 2: *Schematic of a system implementing the new simulation modeling paradigm: a Cyber-Physical Production System incorporating the Digital Twin, CPS*

7 Methodology

Because SMEs are the slowest to adopt the industry 4.0 paradigm, we chose a case aimed at developing Industry 4.0 approaches and methods that can be implemented in SMEs.

Finding case studies through reports of previous studies allows for the exploration and understanding of complex issues and can be regarded as a strong research method, particularly when a thorough and in-depth investigation is required.

In this case, we present a comprehensive study aimed at exploring and reasoning about the global phenomenon of the new simulation modeling paradigm based on the Digital Twin concept, and attempting to draw conclusions about the phenomenon, particularly about the adoption of the new simulation. The paradigm of modeling within the framework of industry projects [17].

8 The case for adopting the new simulation modeling paradigm

Implementing the new simulation modeling paradigm and Industry 4.0 remains a significant challenge for researchers and businesses. There are new ways, however, to demonstrate the integration of built models into general-purpose simulation modeling tools, automate their construction and modification, and implement these solutions without major financial investments, which is a very appealing prospect, particularly for SMEs.

In this chapter, we will look at how the new simulation modeling paradigm is being implemented, from the creation of a new high-level modeling automation methodology to the creation of a digital twin concept for SMEs [17].

9 Case 01: Automated creation of XML templates

The use of a new method of automated DES model building, which uses customer order data obtained via SQL queries to modify the Extensible Mark-up Language (XML) file containing the simulation model, thereby changing the default model structure, is the focus of this paper.

The paper describes the methods and outcomes of a manufacturing process optimization project. The authors built a model that reflects current manufacturing processes and allows them to test optimization methods using discrete event simulation (DES) [22].

Due to a large number of products and manufacturing processes, they developed an automated model building method that builds an ad hoc simulation model using customer order data and the manufacturing process database.

The model and method were put to the test in the optimization task, which involved reducing product travel distance through changes in factory layout and employing a new heuristic optimization method based on force-oriented graph drawing.

9.1 Description of the problem

Creating a static simulation model that covers all possible products (i.e. 30,000) that could be included in customer orders is not feasible because it takes approximately 15 minutes to build a process model for each product, and a model containing 30,000 processes also exceeds the memory limits of the modelling tool used (Analogic, http://www.anylogic.com/).

Manually modifying the simulation model can take a long time, especially if a large number of model variants must be built. In Analogic, the simulation model is typically built by dragging and dropping various blocks and connections onto the canvas. Instead, for each set of open commands, an ad hoc model-building method has been developed. The method involves editing the XML file [19].

9.2 Results

Because orders change on a regular basis, the authors created a method and an application in Java that builds the model automatically from a template, a database of technical procedures, and a database of open or running procedures.

Based on the ordered products and technical procedures, only the necessary machines are placed in the model. Analogic saves models as standard XML files, making it simple to manually or algorithmically modify the model.

The XML simulation model file of Analogic stores information on standard and user-defined blocks and agents, connectors between blocks, statistical monitors, input readers, output writers, and so on.

Data is stored in a tree structure as elements (nodes). An element may have several attributes that describe the element's type as well as any parameters that describe the element's properties. The attributes may contain several lines of programming code describing how the block operates in various situations and states.

The Java application modifies the XML code to modify the machine data and all other relevant abstract objects connected to the machine blocks, such as connectors, sources, and sinks. The Java application reads the blocks in the template file and copies them based on the input data. The following procedure is used to add a new element (block) to the model:

- Locate an XML node that represents a template block.
- Make a copy of the node and connect it to the original node's parent.
- Modify the copied block's data (block name, position on the canvas, block properties, part of the programming code, etc.)
- After that, the resulting XML structure is saved in a new logical file. Figure 4 depicts the transaction role of products and carts, which consists of four main elements:
- Analogic environment simulation model of the basic manufacturing process.
- The layout of the machines and paths was generated from the factory's AutoCAD model.
- A Java program that generates the Analogic XML model from a template file.
- Microsoft Excel as a bridge tool for storing and analyzing input and output data

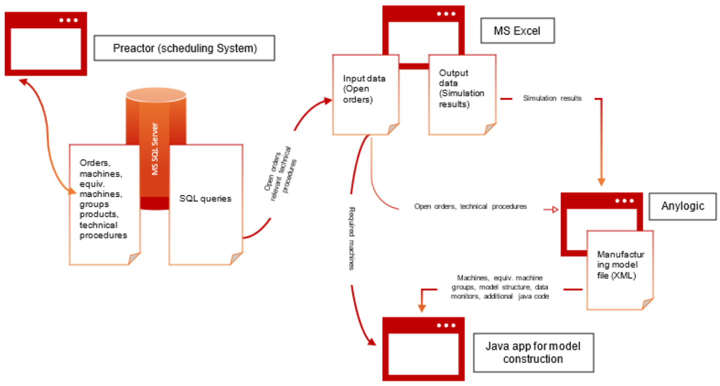

Figure 3: *Schematics of a system implementing automated DES modeling*

10 Case 02: Modelling a virtual factory based on standards

Jain and Le Chevalier describe a method and proof of concept for automatically generating virtual factory models from manufacturing configuration data in standard data formats like XML.

In this context, the virtual factory represents a multi-level high-fidelity simulation. A number of initiatives, such as Smart Manufacturing and Industry 4.0, have identified modeling and simulation as critical to the advancement of manufacturing.

Our proposals include the use of simulation at multiple levels within manufacturing, with models ranging from highly detailed physics-based models of the manufacturing process to high-level DES and SD-based supply chain models.

10.1 Description of the problem

Currently, developing a Digital Twin requires significant resources and expertise, which limits access to large corporations to the detriment of SMEs.

The automatic generation of data-driven models has the potential to reduce the need for expertise, allowing simulation to be used more frequently.

The proposed method extends the scope of the generated model to a virtual factory model rather than a single-level model, and it complements existing automation solutions by proposing the use of standard data formats for the input data describing the manufacturing system in question.

10.2 Results

Analogic is used as a simulation modeling tool in the proof-of-concept method, with multi-level modeling implemented using Java code for the process model, agent-based modeling (ABM) for the machine level, and DES models for the cell/process chain level, a concept similar to that described in (Rodi & Kan- du, 2015).

The integration of the various modeling methods is accomplished using the Analogic tool's native capabilities, resulting in a hybrid model. Historically, hybrid modeling was accomplished by linking models using intermediary software solutions [20].

Figure 4 depicts the proposed method's scheme. The following describes how the proposed automatic generation works:

1. Read configuration data from the manufacturing system using a standard-format interface.
2. Retrieve information from machine parameters and process levels.
3. Assemble the logical network at the plant or cell level using the process plan data as input.
4. Connect the plant or cell level logic network to each individual machine and process.
5. Create the template by using the corresponding templates in the library.
6. Create an installation layout based on configuration data information, with links to the logical network.
7. Run the model with user-specified parameters such as resolution level and output format via the run interaction [21].

The data-based modeling interface works with data in CMSD format, which is based on XML. A Java parser has been created to browse a CMSD file for the machine shop and collect the information required to build the corresponding virtual factory model automatically.

The goal is to generate a virtual factory model automatically using data from the actual factory in the applicable standard formats, with the option of generating output data streams in other applicable standard formats [22].

By generating a multi-resolution model and using standard input file formats, the automatic generation of the virtual plant model is intended to go beyond previous efforts involving the automatic generation of single-level plant simulations [23].

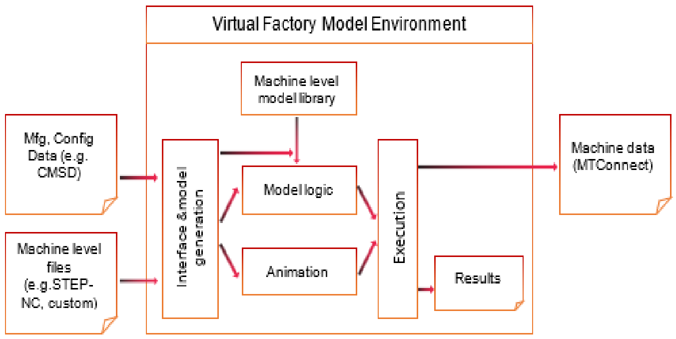

Figure 4: *Standard data format-based modeling automation system schematic*

11 Case 03: Digital Twin for SMEs

Uhlemann et al. (2017) introduce a notion for integrating a Digital Twin of the manufacturing system within SMEs. Their concept is feasible because it ensures adequate data quality while minimizing investment costs and without jeopardizing the benefits of the Digital Twin and CPPS [2].

Their concept includes the proposed database structure as well as guidelines for implementing the Digital Twin in SMEs' production systems. Our additional concept of the Digital Twin for a production process enables the coupling of the production system with its digital equivalent as a basis for optimization with the shortest possible delay between data acquisition and the creation of the Digital Twin [4].

This enables the development of a physical cyber production system, preparing the way for powerful applications. Multimodal data acquisition and evaluation must be performed to ensure maximum agreement between the cyber-physical process and its real model [5].

11.1 Description of the problem

Industry 4.0 methods are still underutilized in manufacturing operations.

Furthermore, the authors describe the following difficulties in realizing the Digital Twin as a necessary prerequisite for a CPPS:

- Manual motion data acquisition is widely used, despite the fact that it conflicts with the required real-time availability.
- Manually acquiring motion data snapshots limits the simulation's potential.
- A central information system is required in conjunction with decentralized data acquisition.
- Internal implementation of Industry 4.0 concepts is frequently inadequate.
- Slow data acquisition standardization in production systems impedes the implementation of agile and adaptable systems.
- Data acquisition standardization has not yet been achieved.
- The high costs of new IT environments are impeding vertical industry 4.0 implementation.
- The coupling of simulation and optimization is insufficiently guaranteed to fully exploit near-real-time models, and there are data security concerns.
- The collection of motion data, in conjunction with data on employee activity and the position and use of production machines, has enormous potential for CPPS implementation.
- Existing time-dependent position data sources and databases are insufficient, particularly in SMEs with a low level of automation.
- A complete picture of the production system can only be obtained with additional information on employee and production resource movement.

11.2 Results

The described concept is novel in comparison to the approaches prevalent in large corporations, which are focused on full automation. Because the production database in SMEs is highly heterogeneous and frequently insufficient for the realization of the Digital Twin. Sensor tracking provides information on the routes and positions of production employees as well as large, highly mobile production equipment.

The necessary technologies and tracking systems based on sensors, as well as extensive program libraries for the implementation of machine vision, are available on the market, making the proposed concept feasible.

Sensor-based tracking should provide information on the routes and positions of production workers as well as large, mobile production equipment such as forklifts, whereas image recognition can detect and identify product types in production as well as smaller machines.

Figure 5 depicts the digital system diagram and the matching concept.

Because of the low level of digitalization of manufacturing data in SMEs, automated collection of machine data is not envisaged.

Furthermore, in the presented concept, the collection of detailed machine data is not required. The concept's innovative aspect is the incorporation of widely adopted and commercially available components that are already available as stand-alone solutions.

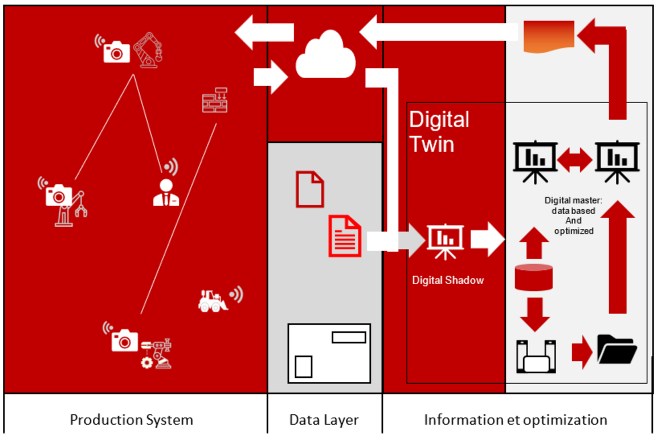

Figure 5: *Concept of the CPPS through the Digital Twin in SMEs*

12 Case 04: Automated modeling based on ERP (Enterprise Resource Planning) data

Kirchhof (2016) describes a practical case in which entire simulation models of complex, large-scale production in a just-in-time manufacturing shop are automatically created from an automotive company's SAP, ERP, and MES systems to support operational planning goals and reduce operational logistics risks.

12.1 Description of the problem

The time and effort necessary to manually create and maintain such a comprehensive model are frequently too great. Manufacturing systems simulation has long been characterized as facing substantial hurdles due to automatic model creation, the resulting decrease in problem-solving cycles, and the requirement for a higher level of data integration.

Operational manufacturing simulation models depend on a lot of input data since they require a high level of modeling. The utility of simulation for operational planning purposes would be greatly increased by the autonomous and on-demand development of type manufacturing simulation models from, for example, business data sources.

12.2 Results

Lean manufacturing practices are widely used in the automobile sector, forcing businesses to strike a balance between cost-effective inventory reduction efforts and operational hazards like stock-outs on the assembly line. In order to analyze and implement countermeasures, the simulation model's goal is to serve as an early warning system and identify probable stock-outs before they happen. As a result, the model's scope includes every internal logistic operation of the business, from the selection of parts in the warehouse to consumption on the assembly line.

The SIMIO simulation program was used to create a general simulation model of the factory floor. A customized SIMIO extension was created to facilitate modeling automation. It enables the modification of a blank model by arranging certain instances of the modeling parts in accordance with the input data. By automatically positioning, linking, and parameterizing the predefined model items in the model, the addon may create whole flow shop models [13].

The company's SAP and MES systems are used to extract the data required to create the model using customized data software that pulls the necessary information straight from the databases of the corresponding systems. The SAP system supplies the necessary data, including workstation specifics, routings, BOMs, shift schedules, production orders, stock levels, machine master data, etc., to model the production line. The manufacturing line and the production process are covered in full by the MES system.

The MES system offers comprehensive data on production sequences, the status of ongoing and planned production, and production order- and workstation-specific production progress. The resulting simulation system assists the company's planning staff in averting logistical issues and production hiccups by being fully integrated into the operational planning process and IT architecture of the business. When compared to a manual approach, automating the models greatly shortens the problem-solving cycle. The approach that is being given works well for complex, large-scale models [27].

13 Case 05: Methodology for automating high-level modeling

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When compared to a manual approach, automating the models greatly shortens the problem-solving cycle. The approach that is being given works well for complex, large-scale models [9].

13.1 Description of the problem

The automation of analysis, training, and solutions is the key obstacle. As the PAs already have in-depth knowledge of civilian transportation networks, they can provide directions alongside the PAs on mobile devices. However, even if the PAs had access to the company's information systems, they would not be able to perform the duties necessary for an experimental design environment because the systems would not be complete and the PAs would not be familiar with the products, processes, resources, and proprietary facilities of an arbitrary company.

Following the paradigm of separating system description from system analysis, the authors made an attempt to automate engineering workflows by creating system descriptions in an ostensibly simpler way and then automatically transforming them into the semantics and syntax of a specific analysis language as needed. The authors, however, discovered that none of the system description languages investigated for production systems was adequate and made the decision to figure out a means to support a multitude of related but distinct languages. The lack of a language for discrete event simulation analysis was another barrier [10].

13.2 Results

The approach outlined by Thiers et al. (2016) places the majority of the transformation intelligence in the model-to-model transformations themselves but takes a small step forward by maximizing the use of model library blocks, which are executable versions of the linking abstraction model elements, to construct simulation models. A middle phase known as the Bridging Abstraction Model will be created to allow the translation of requirements into the model structure.

The Bridging Abstraction Model is an abstract design that captures the fundamental similarities shared by all discrete event logistics systems, including supply chains, warehousing and distribution, transportation and logistics, and health systems.

A system model must be as inventive as necessary for accessibility, the transition abstraction model must be as abstract as possible for robustness and reusability, and efficiency depends on how simple it is to create and maintain mappings between the two. The transition abstraction model is introduced to mediate this fundamental tension between the concrete and the abstract. [11].

The uniqueness of the methodology is found in its approaches and instruments that deal with the main research problems needed to make it applicable to systems engineering, as follows:

• The Bridge Abstraction Metamodel is an explicit, analytically neutral, machine- and human-readable metamodel that encapsulates the fundamental alienations that underlie all discrete event logistics systems.

• Model-to-model transformations: The process has evolved from applying UML stereotypes to declarative specifications in generic transformation languages, such as QVT and ATL, into a tailored model-to-model transformation language and engine (see Figure 3).

• Being aware of the range of production system-related queries and the analyses that can address them. This difficulty is closely related to in-depth expertise in the subject.

- A new difficulty will emerge if and when the methodology's implementation enables a sufficient number of questions about the feasibility to be resolved.

- How to ask the proper questions in order to make effective use of a "question-answer genie," keeping in mind that this would need documenting higher-level processes (diagnosis, continuous improvement, de-identification, etc.) and the questions posed at each stage of their implementation.

The proof-of-concept software created to support the model also provides answers to the following engineering-related questions: - What is the (anticipated) duration (gross cycle time) of a specific (job)?
- What is the typical throughput for doing a particular (task) on a regular basis?
- What is the anticipated throughput of producing a specific (product) in a particular (facility)?
- How many resources at a minimum are required to support a specific throughput?
The concept of the new modeling automation process is depicted in Figure 6.

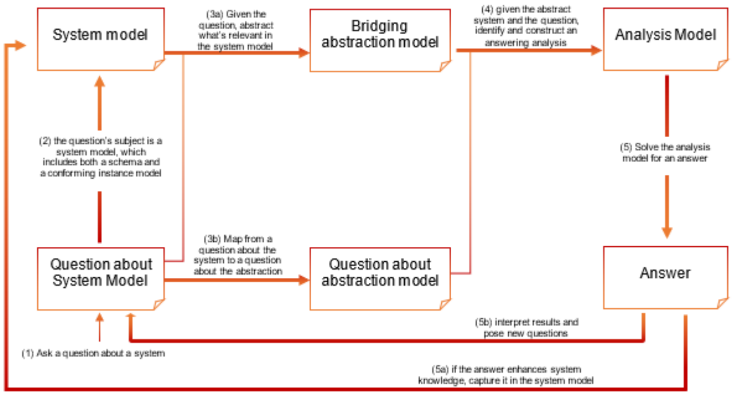

Figure 6: *Novel modeling automation methodology described by Thiers et. al (2016)*

14 Description of results

The Digital Twin for SMEs represents the most effective approach to implementing a new paradigm of alternative approaches that have been established for the fully automated advancement of simulators in correlation with industrial systems in order to develop models of system components at different levels, especially in SMEs.

15 Conclusion

The scenarios studied in this article allow us to draw the conclusion that both large and small businesses are implementing the concept of digital twinning, while there are important distinctions between the issues they encounter and the strategies and tools they employ to address them. The creation of standardized procedures and architectures that would permit integration into their R&D processes and current ERP and MES solutions is a problem for major research companies. SMEs are more focused on using affordable, off-the-shelf simulation modeling tools and commercially available sensors to build proprietary automation that would allow them to implement some of the concepts of energy efficiency than on the purchase or development of automation technologies, likely because of the abundance of resources available.

The only method that could construct the manufacturing process model for a given set of orders in a reasonable amount of time was automated data-driven model development.

Industry 4.0 techniques are currently underutilized in production settings. On the one hand, contemporary publications are addressing the issue of inconsistent definitions of Industry 4.0. On the other hand, there are widespread issues such as a lack of standards and uncertainty over the economic rewards while dealing with the need for often sizable investments.

Aspects of simulation-based engineering and decision support systems can be developed using unique solutions made possible by the research reported in this paper. These methods automate model development and solution identification. The techniques and solutions made available allow for the development of Industry 4.0 automation solutions using the Digital Twin concept and generally accessible sensor technologies, as well as the automation of general-purpose simulation modeling tools using data and standards from ERP/MES.

The process of moving from design to production is one that involves many business considerations. The research findings that have been presented here help this process by allowing designers to understand how their decisions will affect production considerably earlier in the scheduled design cycle than is now achievable.

The multilevel model still faces difficulties with model validation, which can be difficult for automatically constructed models, particularly for multilevel models. The effects of both inherent and extrinsic uncertainty must be taken into account when validating each simulation model.

All physics-based process models must have their application areas established and be evaluated against actual machine operations. As a result of the multi-level model's stacking of validity concerns over multiple levels, one level of this type of model depends on the outcomes of another. Before the virtual factory and other multi-resolution models can be utilized to help industrial decision-making, the impact of the stacking of uncertainty must be recognized and measured.

In order to create integrated multi-level system models, the adoption of a new simulation modeling paradigm in the research environment necessitates tighter collaboration with industrial partners and diversification of researchers' knowledge. The examples given illustrate that there are sufficient integration choices in the current generation of general-purpose simulation modeling tools, therefore the lack of tools is not a problem. Additionally, a variety of approaches have been developed for the automatic development of simulation models that correlate to industrial systems. Barlas and Heavey provide a comprehensive summary of these approaches (2016). The ideas of Industry 4.0 and Digital Twin provide academics with a new incentive for greater collaboration and knowledge transfer between study fields, as multi-level modeling necessitates the integration of models created using various approaches and tools.

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